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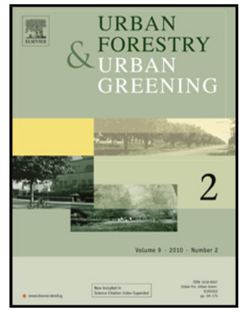

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Role of geospatial technology in understanding urban green space of Kalaburagi city for sustainable planning

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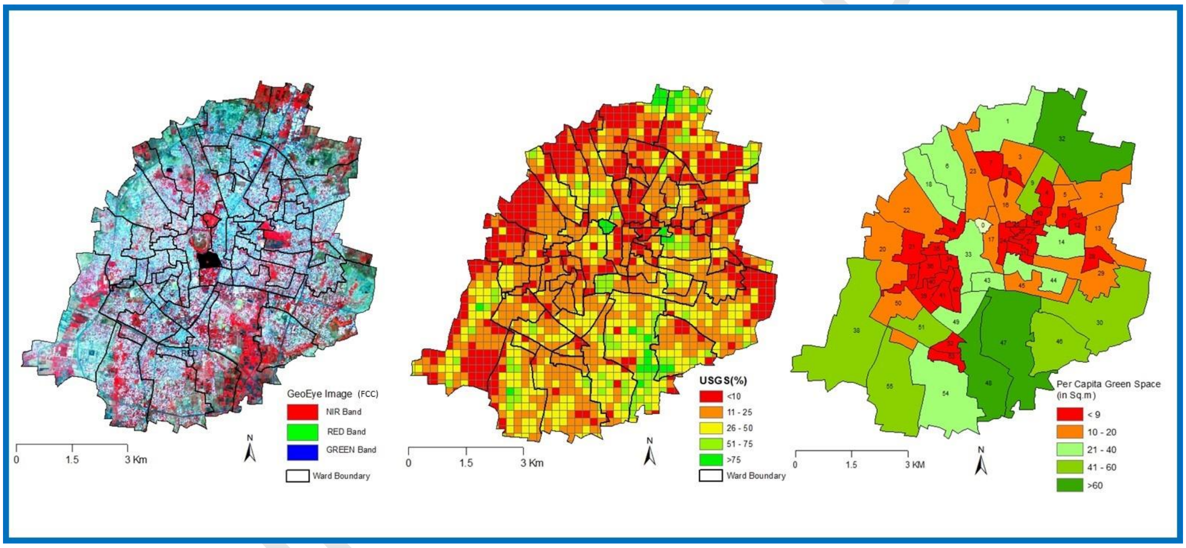
Graphical abstract



Highlights

- Object-based image analysis has been used to prepare an accurate green map of the city.
- Identified critical areas at the micro level to increase green space
- Per Capita Green Space assessment for improving green infrastructure
- Proposed sites for sustainable green planning

1. Introduction

By 2050 the world urban population is expected to nearly double, making urbanisation one of the 21st century's most transformative trends. As the population, economic activities, social and cultural interactions, as well as environmental and humanitarian impacts, are increasingly concentrated in cities, this poses massive sustainability challenges in terms of housing, infrastructure, basic services, food security, health, education, decent jobs, safety, and natural resources, among others (UN-Habitat 2016). Urban green space (UGS) constitutes critical biodiversity hotspots in crowded, concrete-dominated city environments. Despite the importance of these green spaces, they remain little researched in most parts of the world and there's specifically very little information on urban parks in South Asia (Nagendra and Gopal 2010). There is a need for UGS to be established strategically at a landscape scale in order to take advantage of the full range of potential benefits it can bring (Tallis et al., 2011). Mapping and monitoring the changes in UGS is an important task because of the role of UGS in promoting air, climate and water quality, the reduction of noise, the protection of species and the development of recreational activities (Puissant et al., 2014). Currently, two main methods are in practice to assess and quantify UGS. The subjective methods evaluate UGS through visual perception and self-reporting using questionnaires. The second method involves objective measurement of greenness such as the percentage of green area or green space per inhabitant that can be identified using remote sensing techniques (Yuqin Liu et al., 2016). In this study, the UGS has been understood as the layer of leaves, branches and stems of trees that cover the ground when viewed from above; grass, shrubs, lawns and other grass covered areas found in parks, golf courses and playgrounds (Marvin Bauer, 2011).

The benefits of the tree canopy, ground covers and turf grasses are increasingly well known (Beard and Green, 1994; O'Neil-Dunne et al., 2014; Ruggeri et al., 2016). The UGS has been highlighted as offering mitigation potential against atmospheric particulate pollution (Tallis et al., 2011) and also filters air pollution and facilitates physical exercise, fresh food production, and better mental health (WHO 2012). It plays a very significant role in urban planning, environmental protecting, and sustainable development policy making (Zhang and Feng, 2005; Marvin Bauer, 2011; Roy et al., 2012; Razieh et al., 2016). The existing research of urban green areas and their sizes, qualities and areal changes over time have been focusing on urban greenery in general and rarely on urban lawns (also called grasslands, turf grass, meadows) although lawns are common in cities all over the world (Hedblom et al., 2017). In recent years, scientists and policymakers have been increasingly calling for large extent measures of lawns and other similar landscape features (Giner et al., 2014). They also emphasize the need for adequate number of trees as environmental infrastructure in the urban areas to address growing environmental issues (Singh H.S, 2013). Quantitative identification of physical changes to and the development of urban green space is considered as a critical first step in planning sustainable urban development (Beiranvand et al., 2013).

Very high resolution remotely sensed imagery is an effective data source for analyzing the urban environment (Du et al., 2014) and planning (Li et al., 2012). Urban tree cover (the proportion of area when viewed from above, occupied by tree crowns) reveals the extent and variation of the resource across a city (Nowak et al., 1996). With the development of, and innovations in, data technologies, and theories of the wider arena of earth observation, urban remote sensing has rapidly gained popularity (Du et al., 2014). Remote sensing canopy assessment is reasonably simple and can be conducted quickly and inexpensively (Moskal et al., 2011) and it can give an accurate and comprehensive assessment of the structure and benefits provided by urban forests (Dwyer and Miller, 1999).

Many research studies have proved the efficiency of geospatial technologies in managing green resources (Johansen et al., 2011). Remotely sensed data have been used to map urban land cover for many decades (Zhou et al., 2006; Moskal et al., 2011; Li et al., 2012). Monitoring forested areas using digital remote sensing offers a faster, repeatable, objective, and efficient way of managing urban forest dynamics at the landscape level. Additionally, image-based methods can potentially enable mapping of larger areas using the increasing number of temporal databases provided by satellite imagery (Myeong et al., 2006). Object-Based Image Analysis (OBIA) has become increasingly popular in recent years (Blaschke 2010; Johansen et al., 2011; Moskal et al., 2011; Li et al., 2012; Alqurashi et al., 2016; Gu et al., 2016; Kaszta et al., 2016) and OBIA methods can generate good and repeatable Land Use Land Cover (LULC) classifications suitable for tree cover assessment in urban areas (Moskal et al., 2011). The efficacy of OBIA in forest resource mapping, monitoring and managing is discussed in Blaschke (2010). OBIA has many significant advantages over other methods for classification of urban or forest ecosystems (Ouyang et al., 2011).

Remote sensing and Geographic Information Science/Systems (GIS) are widely used in governance and planning at national, regional and local scales (Zlinszky et al., 2015) and have the potential to provide accurate information on LULC changes (Shekhar,2007; Alqurashi and Kumar 2013). Tools such as GIS allow for large-scale assessments for open-space planning. These spatial analyses and inventories provide current, comprehensive information vital to open-space decision-making and identify opportunities for a coordinated effort to guide urban development in a manner that will take advantage of all the social and ecological functions offered by the urban forest (Dwyer and Miller,1999; Singh et al., 2015).

Information about the presence and the change in the layout and abundance of urban vegetation is most useful in modelling the behaviour of urban environments (Zhou et al., 2014). Tree-planting programs need a comprehensive assessment of existing tree canopy, a baseline documentation that supports establishment of specific community goals. Traditional methods are laborious and field-based methods are generally sample-driven and lack adequate detail for entire municipalities. Moderate-scale tree canopy maps developed from remote sensing data are also lacking the needed specificity for evaluation of neighbourhoods with sparse tree canopy. Ideally, tree canopy maps will be accurate to the scale of individual trees, permitting analysis of municipalities at a range of scales from broad political units (e.g., city, county, or state) to individual property parcels.

Despite these potentials and opportunities, there is a large gap between theoretically available information and the actual information extracted from remote sensing imagery to support decision-making processes (Benz et al., 2004). The present study aims to bridge this gap. A robust methodology has been developed by using very high-resolution remote sensing data and OBIA methods to extract urban green space. The contributions from this study can be used as an input for further planning to improve the green infrastructure of Kalaburagi city.

In this paper, we describe the basic concepts behind our approach, the physiognomy of the study area and explain the adopted methodology in detail. We quantify the urban green space and create a green map of Kalaburagi city. We analyse the results of the urban green space index and investigate the distribution of urban green space at meso (administrative ward) and micro (200m x 200m grid) levels to identify the critical areas of urban green space. We identify the inequalities in per capita green space and discuss future urban green planning possibilities in the study area. Accordingly, this paper contributes to the existing literature and analyses disparities in urban green space at the micro level for improving the urban green space of Kalaburagi city in order to provide quality urban life to its citizens.

2. Materials and Methodology

2.1. Study Area: Kalaburagi City

'Kalaburagi' (formerly known as Gulbarga) which means stony land in Kannada (the regional language of the State of Karnataka, India) is a growing city situated in the north-eastern part of Karnataka State (Figure 1), India. It is the administrative headquarters of Kalaburagi District, which has a very long history dating back to 6^{th} century AD. Kalaburagi city has an area of 64.00 km^2 (Shekhar, 2016). The climate is generally dry with temperature ranging from 20^oC in the winter to 45^oC in the summer, and an annual rainfall of about 750 mm.

The city is undergoing rapid changes in terms of population growth as well as in the degree of urbanization. Since the city is located in the economically underdeveloped region of Hyderabad- Karnataka, it became a nodal center for many development activities (Ramachandra T.V. and Bharath H. Aithal,2012; Shekhar,2013; Shekhar,2014). Kalaburagi has a population of 0.54 million having grown from 0.43 million in the year 2001 (Table1). The city has 55 administrative wards and three urban outgrowths (Census of India, 2011). Urban forestry, protection of the environment and the promotion of ecological aspects are the main functions of the Municipal Corporation of Kalaburagi city.

Due to increasing urbanization, there are notable changes in the land use pattern of Kalaburagi city and the area under parks, playgrounds and gardens has decreased from 12.57% in 1981 to 6.56% in 2011. Most of these open areas were converted to residential use because of increasing demand for housing (Mathad,2015). Vegetation cover of the study area assessed through Normalised Difference Vegetation Index (NDVI) in another study using Landsat data, showed that the area under vegetation had declined by about 19% from 1973 to 2010 (Ramachandra T.V. and Bharath H. Aithal, 2012). Land use analysis of Kalaburagi city showed that the percentage of parks and open spaces is 6.56 percent

(446.56 ha, 2011) of the total geographical area of the city (Mathad, 2015). Due to the hot dry climate of the city, the type of vegetation found here comprises grasses, thorny xerophytic shrubs, and trees like *Acacia sp., Azadirachta indica A. Juss, Ficus benghalensis L., Thevetia peruviana (Pers.) K. Schum., and Tamarindus indica L.* (Patil,2012).

2.2 Data

In the present study a very high-resolution image GeoEye data was used to extract the urban green space of Kalaburagi city. The GeoEye Foundation provided satellite imagery (Nine tiles of each PAN and Multispectral data that covers Kalaburagi city and its surroundings) based on the request of the authors who outlined their research goals and objectives. Imagery is provided to support targeted research or environmental projects over specific areas on the Earth. The details of satellite data used for the current study are summarised in Table 2. The ward map of Kalaburagi city is based on the administrative units of Kalaburagi City Corporation as shown in the land use map of Kalaburagi city prepared by the Kalaburagi Urban Development Authority. The 2011 census data of Government of India was used to study the population density and per capita green space availability. Primary data included the data (GPS locations of green cover, geo-tagged field photographs) collected during the field visit for accuracy assessment and validation of final results.

2.3 Methodology

The methodology comprises 5 major phases (Figure 2). The first phase consists of basic image preparation that includes mosaicking the tiles of the satellite image, pan sharpening, and the creation of the image subset by using Erdas Imagine 2014 software. The second phase is OBIA. This includes image segmentation and extraction of urban green space by using fuzzy rule based classification in eCognition software. The third task is accuracy assessment. That actually involves the selection of sample objects and assessing the accuracy of the results of OBIA in the eCognition environment. Creation of base layers and GIS analysis together form the fourth major task and that involves preparation of the ward map of Kalaburagi city, and 200mx200m grid zones map and GIS analysis (4 in Figure 2). The analysis includes intersecting urban green space with ward/grid zone layers. The final part involves calculating the Urban Green Space Index (UGSI) both at the meso and micro levels and per capita green space. Lastly, the interpretation of the results and a discussion of the current scenario of urban green space (UGS) in Kalaburagi and suggestions for green planning.

2.3.1 Image preparation (Phase 1)

This includes the first phase of the overall methodology flow chart (1 in Figure 2). The subset of GeoEye image of Kalaburagi was prepared from the mosaic layer of pan-sharpened GeoEye data. There were 9 tiles of each PAN and Multi-Spectral (MS) image received from the GeoEye Foundation for this research purpose. By using 'Mosaic Pro' application of Erdas Imagine software, all 9 tiles of multi-spectral images were combined into a single colour balanced and compressed ortho-mosaic imagery (Imagine, 2014). Pan-sharpening was carried out using subtractive resolution merge algorithm since this algorithm was designed specifically to provide a fast solution and is a radiometrically accurate technique for merging Pan with MS data (Imagine, 2014). Especially, it was designed for Quick bird, Ikonos and Formosat images that have the simultaneous acquisition of the pan and MS, with all 4 MS bands present, and a ratio between the MS and pan image pixels' sizes of approximately 4:1. This method was therefore ideal for the GeoEye data with 41cm (Pan) and 165cm(MS) spatial resolution and the pan sharpening helped to enhance the spatial resolution of MS images. Based on the city limit, the subset was created. The subset image was used for image classification in eCognition software version 9 environment. For object-based image classification, the reflectance values of all four bands were used and the necessary index was prepared using NIR and RED bands, for NDVI calculation (Formula 1).

NDVI is useful in detecting the surface features of the visible area which are extremely beneficial for municipal planning and management (Bhandaria et al., 2012) and beneficial for policy makers in decision making (Gandhi et al., 2015). NDVI is sensitive to the greenness of vegetation and is the most commonly used vegetation index in various vegetation studies (Yusoff and Muharam, 2015). The NDVI algorithm takes advantage of the fact that green vegetation reflects less in visible light and more in NIR, while sparse or less green vegetation reflects a greater portion of visible light and less in NIR. NDVI combines these reflectance characteristics in a ratio (Genesis et al., 2014). NDVI values are between 0 and 1, having a sensitive response to green vegetation even for low vegetation covered areas. This index is often used in research related to regional and global vegetation assessments and was shown to be related not only to canopy structure (JinruXue and Baofeng Su, 2017). NDVI is also useful for general cover monitoring regardless of more localized soil and vegetation variation (Amiri et al., 2010). NDVI was found to be highly correlated to percent cover of many species (Ruggeri et al., 2016) and also NDVI gives the best estimate of the percentage of vegetation cover for a wide range of grass densities (Purevdorj et al., 1998). Using NDVI for image classification to classify vegetation lets better results be achieved (Tamta et al., 2015). But the efficiency of a given method at isolating and segmenting individual tree crowns varies with the characteristics of the forest itself (Singh et al., 2015). NDVI values are region- and season-specific (Jiménez-Muñoz et al., 2009).

In the present study, the calculation of NDVI has been carried out as a customized arithmetic feature with the following formula.

$$NDVI = (NIR - RED)/(NIR + RED) \qquad (1)$$

Where,

NIR = Reflectance in Near-Infrared Band (780 - 920nm)

RED = Reflectance in Visible Band (655 - 690 nm)

NDVI used in an OBIA fuzzy membership classification approach to map vegetation land-cover classes resulted in relatively high classification accuracy (Bao et al., 2014).

2.3.2 Image segmentation and classification (Phase 2)

Image analysis is carried out using Object-based Image analysis (OBIA). OBIA-based methods have a wide range of applications, ranging from landscape-based analysis to individual tree crown delineation. Object-based classification will outperform both supervised and unsupervised pixel-based methods (Weih et al., 2010) and Markus Immitzer et.al., (2012) tested and confirmed the superiority of the object-based approach over pixel-based classification. Using OBIA for vegetation mapping has increased recently (Moskal et al., 2011; Du et al., 2014; Aryal et al. 2014; Husson et al., 2016; Lindquist and D'Annunzio 2016). Rule-based classifier has been successfully utilized by a number of researchers (Sridharan and Qiu 2013). Rule sets are knowledge-based expert systems in which, the knowledge is translated into an automated workflow to extract information from the data. In the present study, urban green space was extracted by using a fuzzy rule set based classification and it was implemented using eCognition software. Table 3 shows the details of the rule set developed in the present study to extract green space. This process represents phase 2 of the methodology.

The basic processing units of OBIA are segments, also known as image objects. Determining the appropriate scale of image objects is one of the most important and critical factors affecting the quality of segmentation (Bao et al., 2014). Therefore, lots of trials were done based on the available literature and the segmentation results to determine the scale (30 for the present study) for basic segmentation. The initial multi-resolution segmentation is the most commonly used approach (Singh et al., 2015) and provided image object primitives (seed - objects) with certain spectral behaviour, shape, and context. A single image object may represent an individual tree crown or several overlapping tree crowns and also a vegetation-covered region with the mixed tree, shrub, and grassland (Zhou et al., 2014). NDVI and Brightness were among the most important spectral variables (O'Neil-Dunne et al., 2014) used to classify the image objects into two major classes - 'Green' and 'Others' (Non-green) and the class descriptions are given in Table 4. The description of land cover classes used by Marvin Bauer (2011) has been found more appropriate than others and hence the same has been followed to classify the satellite image in the present study.

After this step, the classification result was used as a high-level input for classification–based segmentation. This second level segmentation helps to extract objects of interest through iterative loops of classification and processing (Benz et al., 2004). During this step, chess board segmentation was used as second level segmentation to create image objects (size 4) from class 'Green' at the image object level. Then NDVI and Max.Diff were the most important spectral variables used to refine the image objects and to remove the false positives (Non-Green objects classified as Green objects in the previous steps).

Hence, in the present study, two different segmentations were used for image segmentation since the object primitives of the first segmentation (Multi-resolution) underwent a classification based segmentation (chess board) for green cover extraction at a fine scale. Once satisfied with the cleaning of image objects, basic reshaping (merge) and advanced reshaping (morphology) tools were used to get proper object shape (tree crown and ground cover) and finally the 'Green' objects were exported to the GIS environment as a .shp file.

2.3.3 Accuracy assessment (Phase 3)

Accuracy assessment is necessary to validate the results (Gu et al., 2016). It compares the classification result with ground data to evaluate how well the classification represents the real world. A detailed review of classification studies in urban areas showed that Ikonos and Quick Bird data because of their sub-meter spatial resolution were used to map vegetation cover at a local scale and the sample polygons created from the high resolution (VHR) data were used for validation purpose or for accuracy assessment (Xie et al., 2008; Matikainen and Karila, 2011). Therefore, the sample objects were selected from GeoEye image through visual interpretation and field verification by using "*Classification menu -Samples –select samples*" in the eCognition software and were used for validation of the result. Since there is no universal agreement on the best sampling unit (Julien Radoux and Patrick Bogaert, 2017) the sample image objects were selected to be as significant representation of the study area.

The standard practice consists of reporting the map accuracy as an error matrix (Julien Radoux and Patrick Bogaert, 2017). By using eCognition, "*Tools - Accuracy assessment"* menu, '*error matrix based on samples statistics'*, classification accuracy was calculated with these samples (not pixels). The match between the sample objects and the classification is expressed in terms of parts of class samples. For calculating 'error matrix based on Test and Training Area (TTA) mask statistics', the manually selected sample image objects were converted into TTA mask. The test areas were used as a reference to check classification quality by comparing the classification with reference values (called ground truth in geographic and satellite imaging) based on pixels (eCognition User Guide, 2014).

2.3.4 GIS layer preparation and UGS analysis (Phase 4 and Phase 5)

This phase includes the base layer preparation in the GIS environment. ArcGIS 10.4.1 was used for preparing the file geodatabase and Ward layer of Kalaburagi city. The grid zones layer (200mx200m) was prepared for micro-level analysis. The result of the image analysis from eCognition was exported onto the same geodatabase for further analysis. The overlay analysis helped to intersect the green space with ward boundaries and grid zones. The 2011 census population data was used to create the population density map.

An Urban Green Space Index (UGSI) was developed to quantify the urban green space. The index explains the amount of green space within a spatial unit (ward/grid zone) and it is expressed as a percentage. The percentage gives interpreters a means of comparison and standardization when evaluating predefined areas (Nowak et al., 1996). The formulation and computation is adapted and modified as follows

UGSI for i^{th} spatial unit can be expressed as:

$$UGSI_i = \frac{G_i}{A_i} \qquad (2)$$

Where,

G_i = Green space in spatial unit i

A_i= Area of the i^{th} spatial unit, where $i = 1$ to n

The total sum of UGSI (in %) of all the spatial units is expressed as:

$$UGSI_T = \left[\frac{\sum_i^n G_i}{\sum_i^n A_i}\right] \times 100 \qquad (3)$$

After calculating the UGSI, the results were exported as .jpeg maps for interpretation and discussion.

The Per Capita Green Space ($PCGS_i$) for i^{th} spatial unit was calculated by dividing the green space of i^{th} ward and the total population of the ward *i* as per the developed formula 4.

$$PCGS_i = \frac{G_i}{PNi} \qquad (4)$$

Where,

G_i = Green space in spatial unit *i*

PN_i = Population in spatial unit ii

3. Results

OBIA methods are making considerable progress towards a spatially explicit information extraction workflow, such as is required for spatial planning as well as for many monitoring programs (Blaschke, 2010). Rule-based classification approaches can yield good results but the problem is, the development of rules is time-consuming and new datasets or changes in the characteristics of the datasets require changes in the rules (Matikainen and Karila, 2011). It was therefore decided to develop a simple rule set with limited feature attributes.

3.1 Image-based analysis: classification results

The results derived from GeoEye data showed very high accuracy with an overall accuracy of 97.3% for samples and 99% for Test and Training Area (TTA) and the error matrix is given in Table 5a and 5b.

In the present study, to evaluate the classification results of OBIA, three approaches were used. First of all, a visual comparison of the classification results was made between the original image and the classified image. Secondly, the ground truth data which can support the cross-validation of results at the region of interest level (Johnson, 2015). Therefore, qualitative validation was made in the field by comparing the dataset with the real land cover in different points. Figure 3 shows a glimpse of the validation of results with ground samples by adding geotagged field photographs to Google Earth imagery through GeoSetter, an open source software. It showed the classification results were very good. After that quantitative validation, the accuracy assessment was carried out in eCognition and the confusion matrix (Table 5a and 5b) showed very high accuracy both in samples and Test Training Area analysis.

The classification results from GeoEye are shown in Figure 4. The main algorithm used for classification of green class was NDVI. NDVI values were negative for non-green objects (others) including water and building, roads and thus green space was easily separated from them (Barnett, Beat, et al. 2005). Therefore, the image objects were classified into either ‘green’ or ‘others’ and no unclassified objects.

3.2. Results of GIS analysis: UGSI

3.2.1: Ward level analysis

The green objects extracted from OBIA were then exported to a GIS environment for calculating the UGSI. The urban green space layer was added to the File geodatabase consisting of the ward layer and the grid-zone layer. The ward layer represents the administrative units of Kalaburagi Municipal Corporation and the grid zones were generated as 200mx 200m areas. The purpose of this layer is to understand the UGSI at the micro level for green planning.

By using Overlay operations, the green layer was intersected with the ward layer to get the green area per ward (an administrative unit of City Municipal Corporation). By using the

UGSI formula, the urban green space index for all the wards was calculated (Figure 5). The table 6 presents the quantification of urban green space at ward level.

According to the Government of India, National Forest Policy of 1988 and the draft National Forest Policy published in 2016, to maintain the stability of ecosystem a minimum of one-third of the total land area (33%) should be under tree cover. This notion has been kept as a base for interpreting the urban green space of Kalaburagi. This shows that out of 55 administrative wards, 5 wards come under the critical category, where the percentage of urban green space is less than 10% with a minimum of 8%. 4 wards come under satisfactory condition having more than 33% of the area under green space. The only spatial unit which has more than 66% of green cover is a dry pond (a small stagnant water body) area and surprisingly this area is not included in any of the administrative wards and shown as a separate entity by Kalaburagi Urban Development Authority (KUDA) land use maps. Therefore, the average green space of Kalaburagi city is 19.44% excluding the dry pond area.

3.2.2 Grid zone level analysis

As the uniform grid zones are easily compared, the urban green index for grid zones was calculated by intersecting the green layer with grid zones. The grid zone layer was created by using 200mx200m grids.

The grid zone map gives a detailed understanding of urban green space at the micro level (Figure 6). The 55 administrative wards were divided into 2277 grid zones. Out of 2277 zones, 672 zones were exactly 200mx200m (area =40,000m^2) and the rest were little smaller depending on the shape of the wards since the ward map had been used to intersect the grid zones. The logic behind this was, the ward is an individual identity in the Municipal administration and each ward has its own Corporator, an elected member of the municipal corporation and planning will be done at the ward level. When a grid zone is shared by two or more wards, planning will be difficult and appropriate decisions may not be possible for the administration. Hence the UGS was studied at micro level within the ward boundary and the issue of improving the green cover and green planning was taken at ward level. The micro level study revealed that out of 2277 grid zones, 733 grid zones have less than 10% of the urban green space (table7), and only 52 zones are above 75% green area. The average green space is 21.3%.

3.2.3 Per Capita Green Space

The World Health Organization (WHO) has suggested that every city should have a minimum of 9 m^2 of green space per person. An optimal amount would sit between 10 and 15 m^2 per person. This measurement of Per Capita Green Space (PCGS) can give better understanding of urban green space in a city. Hence by using the developed formula 4, the PCGS was calculated for Kalaburagi city.

The comparative study (Figure 7) between the population density and the per capita green space clearly indicated that there is a negative correlation between population density and the per capita green space. The high-density wards have less per capita green space. and the outer wards in the southern side which have relatively low density have high per capita green space. Therefore, attention should be paid to the inner wards, which have high density of population and tree plantation should be encouraged to maintain the healthy environment.

As per WHO standard, there are 25 wards that come under the critical value (table 8) since they have less than 9 m^2 PCGS. Only 9 wards have a per capita green space greater than 40 m^2. The inner wards have less green space compared to the wards close to the city limit. With increasing urbanization, proper planning has to be done to improve the per capita green space at ward level.

4. Discussion

4.1 Relevance of this study

In the present study urban green space maps (to the scale of individual trees) have been prepared for Kalaburagi city (for the entire limit of Kalaburagi Municipal Corporation). This is probably the first time that Kalaburagi city is going to have a green map of this scale and it will certainly help in green planning to improve the green infrastructure.

The UGSI used in this study is slightly different from Green index used by previous studies (Schöpfer et al., 2004; Gupta et al., 2012; Senanayake et al., 2013) in the sense that the study on Salzburg Council area (Schöpfer et al., 2004), the Green index was calculated based on urban structures in terms of greenness and integrated the individual perception about green space. In another study on Delhi (Gupta et al., 2012), by using IRS LISS IV (5.8m spatial resolution) data the green index was calculated as the percentage of green in each cell, based on binary classification (green and non-green classes) of NDVI measurements. That was a pixel based approach and the quantification was neither done at administrative unit level nor went up to individual tree level. Another study on Colombo (Senanayake et al., 2013) by using the THEOS satellite which has 2m spatial resolution had a similar approach of studying the green space at administrative unit level but not at grid level. Hence this study is an earnest effort to extract the urban green space from a very high-resolution data at micro level.

In the present study, the urban green space was extracted from very high resolution data in OBIA environment and UGSI was quantified by the developed formula. The green space map shows the percentage of green space in each ward and also the micro level study gives the details of green space in 200mx200m grid level. This analysis therefore helps identify the wards which are lacking in green space and also within the ward, where it can be improved further. The Per capita green space analysis revealed that 25 wards out of 55 lack the minimum per capita green space recommended by WHO for healthy living.

4.2 Variations in the green spaces of Kalaburagi city

Urban vegetation plays a very important role in urban planning, environmental protection, and sustainable development policy making (Zhang and Feng, 2005). The city of Kalaburagi is located in a tropical latitude and has a hot dry climatic condition with scanty rainfall by nature. Thus it did not have thick vegetation and only limited tree growth. Overall urban green space is less and out of 55 wards, 50 wards have an UGSI of less than 33%. It is critical and efforts should be taken to improve the green space of Kalaburagi city. The average per capita green space of 24m^2 is relatively good but the city is growing and the population will keep on increasing (Census of India, 2011). This needs to be taken care of there are a lot of constructions and conversion of open and agricultural areas into built-up area (Shekhar, 2016) which results in the reduction the existing urban green space.

Geographically the central part of the city holds the Abba lake and a fort surrounded by a good number of trees. The dry pond area located north of the fort is fully green. The park nearby the lake also has good lawns and trees. Next to this in the eastern side, lies the CBD of Kalaburagi, the market area and this has less green space. The west side of lake area has low income settlements/ slums and has less to moderate green space. The peripheral areas in the north western part of city have very less green space. The south east part has moderate to high green space with farm lands dotted with trees. Other than this, there are few green patches present in the northern part of the city and north of the city market area.

The proposed land use map of Kalaburagi city has some areas devoted for parks and play grounds as per the 2020 plan and if they are going to be used to improve the green space, there will certainly be an increase in the per capita green space and over all urban green space. The grid zone map with less than 10% of urban green space overlaid on the GeoEye image of 2013 and verified with Google earth Image of 2017 also showed that there are ample opportunities to improve the percentage of green space in those zones (Figure 8).

The available open space in the city of Kalaburagi is an advantage to the planners and other stakeholders and if we plan for suitable species, there are chances of improving the green infrastructure. The city corporation can improve the existing parks and open spaces by planting more trees and protecting it from encroachment. The wards which have less than 10% of urban green space and less than 9 m^2 per capita green space should be given priority and trees should be planned along the roadside, streets and private gardens should be encouraged. The Green India Mission (GIM), one of the missions under India's National Action Plan on Climate Change (NAPCC), has recognised the role of urban trees in creating a healthy environment has aimed to enhance tree cover in the urban and peri-urban areas in over 200,000 ha in a decade by 2020 (Venkataramani, 2015). The Municipal Corporation has taken initiatives to improve the green space through 'Brindavana Pavitravana' program and through social forestry scheme. It has been planned that the forest department will provide 10,000 saplings under these schemes to improve the green space. To take up the urban forestry programme, the corporation had allocated Rs.40 lakhs (4 million) in its 2016-2017 budget. Through a people volunteer program, people could participate and plant a sapling by donating Rs 2500/- per sapling. The 2020 development plan of Kalaburagi city also tries to maintain the existing green space and plans to increase the number of public parks/ gardens to bring healthy air to the city.

4.3 Limitations

Mapping vegetation at individual tree scale in an urban area using high-resolution data is a severe challenge to decide the scale parameters because the vegetation-covered surfaces are often surrounded by buildings and other urban facilities resulting in locally random radiation noises superimposed on their already very complex layout (Zhou et al. 2014).

Though the mapping was carried out to the individual tree level, the urban green space was not differentiated into various types of green space and also various types of trees (trees of various species), shrubs, bushes, and grasses. That would have added value to the green maps.

5. Conclusion

Urban vegetation plays a crucial role in sustainable urban planning and environmental protection. Lot of studies proved time and again that enhancing green space certainly enhances the quality of urban life.

The present work has shown that OBIA can be used to generate a high-quality map of urban green space like the previous studies. This study of Kalaburagi city is the first of its kind using very high resolution data and OBIA to quantify the urban green space at the micro level and at the per capita level. This study has also demonstrated that high levels of accuracy can be with a detailed green map of Kalaburagi city at the individual tree level. This map will be used to identify the critical areas at ward level and the grid level. The outcome of this study will form the basis for future green planning since it has shown the existing scenario of green space in the city at ward level and at grid zone level with an average green space of 21.3% and per capita green space of 24m^2. It could identify the critical area (less than 10% of UGS) which need immediate attention and also give an idea regarding the scope for improvement in those areas by studying the proposed land use map. The present green map will be shared with the local administration for green spaces planning and thus play a crucial role in improving the environmental quality and standard of living of the residents.

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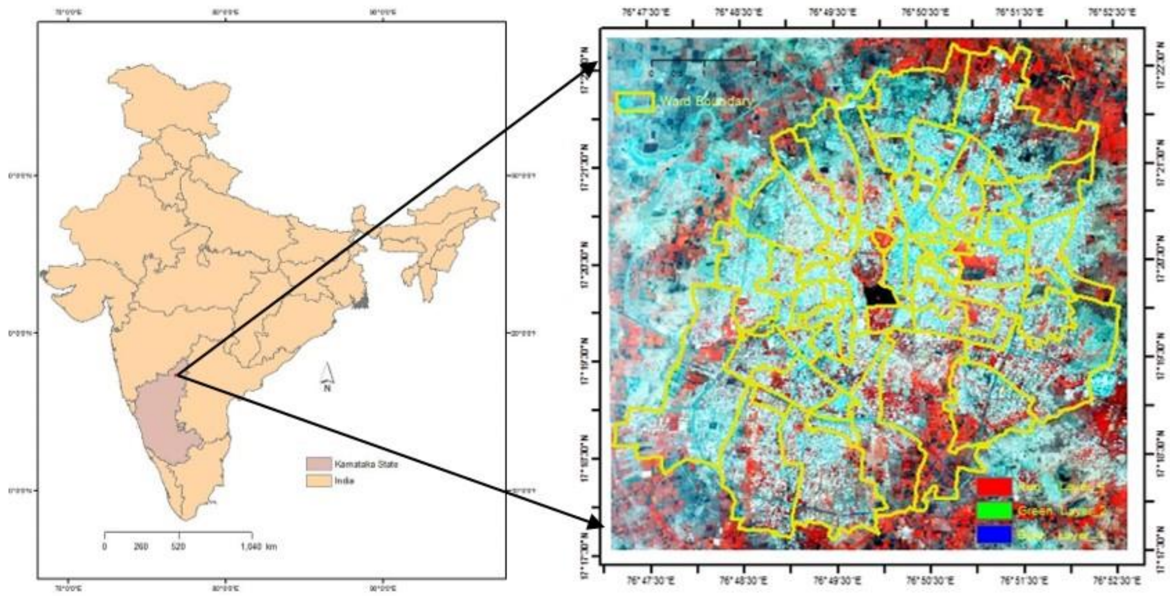
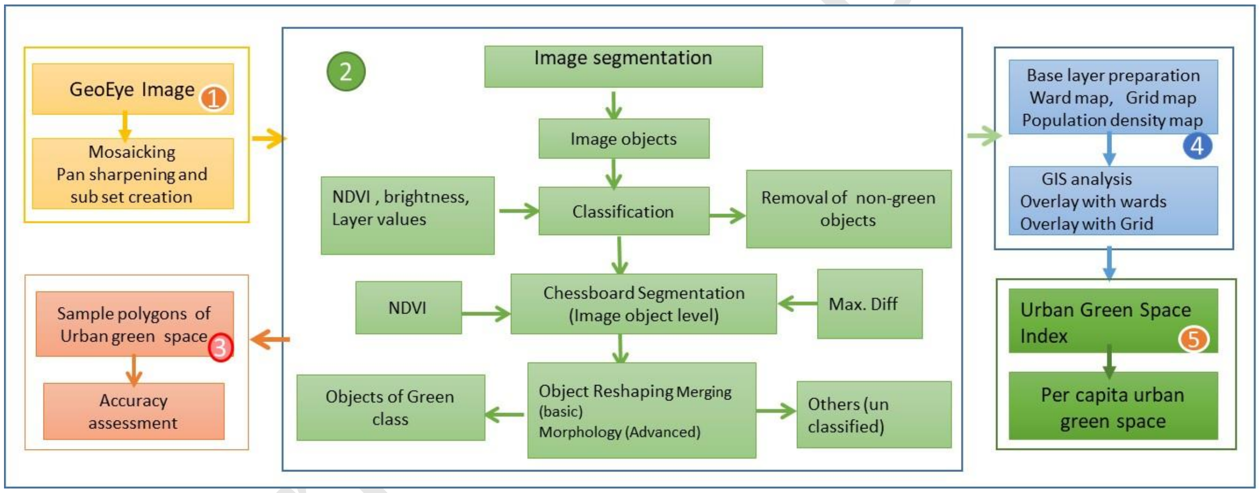


Figure1. Location map of Kalaburagi city with administrative wards



1. Image Processing
2. Object Based Image Analysis (OBIA)
3. Accuracy Assessment
4. GIS layer preparation and GIS analysis
5. Green Indices

Figure 2. Overall Methodology workflow

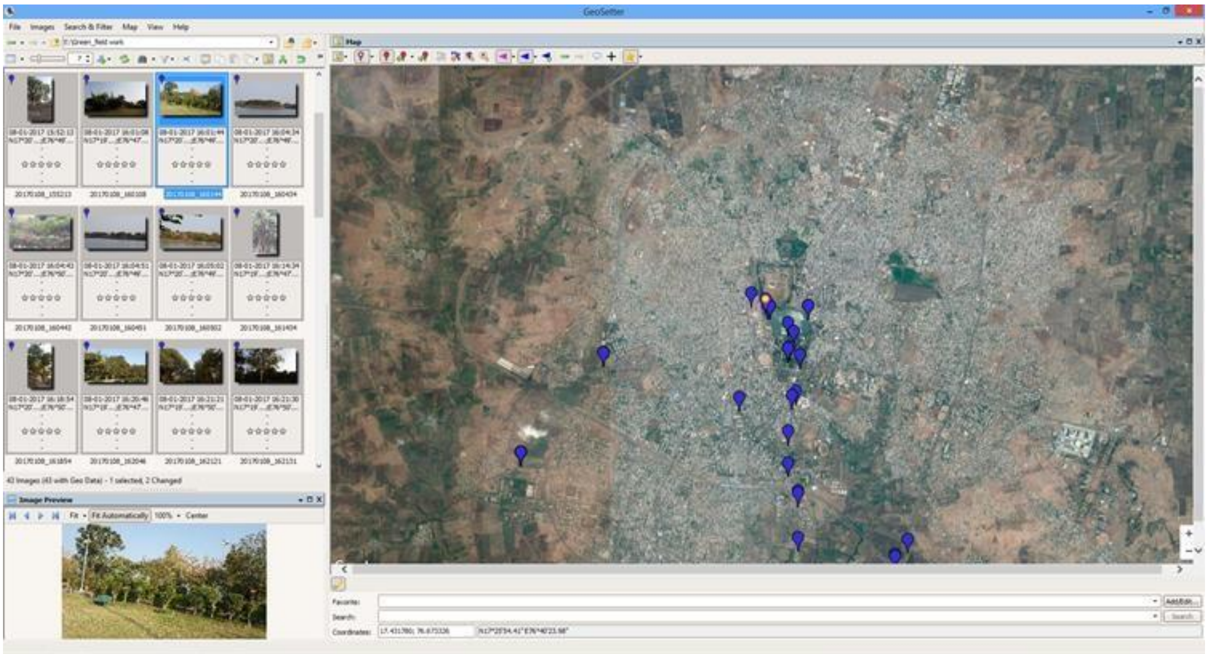


Figure 3. The snapshot from GeoSetter (Open source Software) display the validated areas and the field photographs (Geotagged) in the background of Google Earth Image

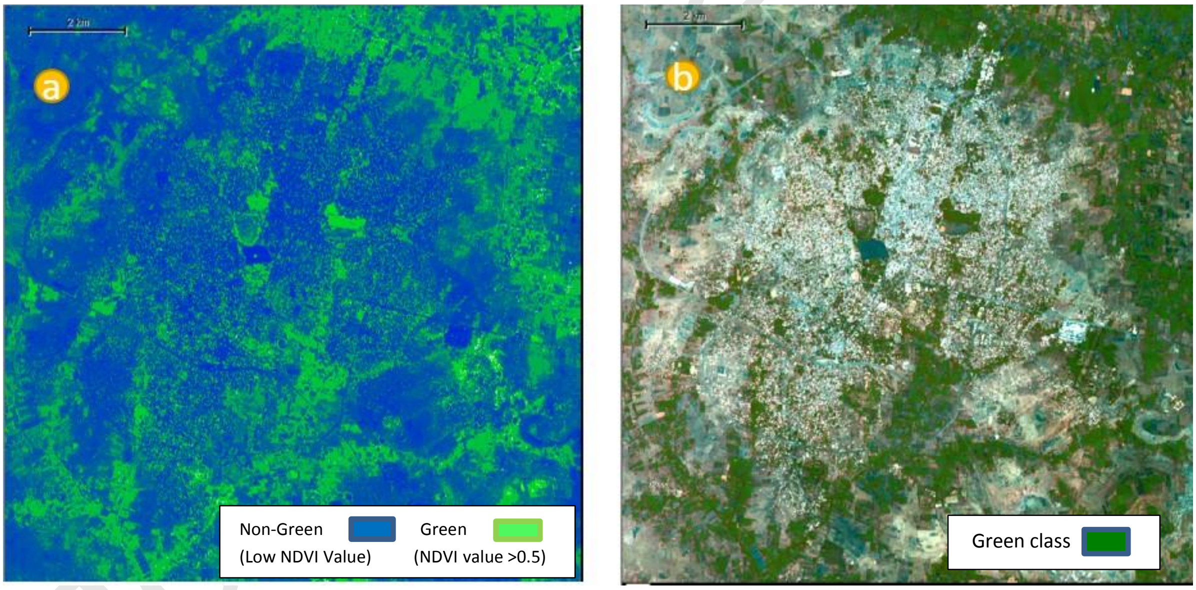


Figure 4. Image classification from GeoEye: a) NDVI feature view in eCognition Developer b) classified image with class "green" c) a closer look on false colour composite of GeoEye image and green classification

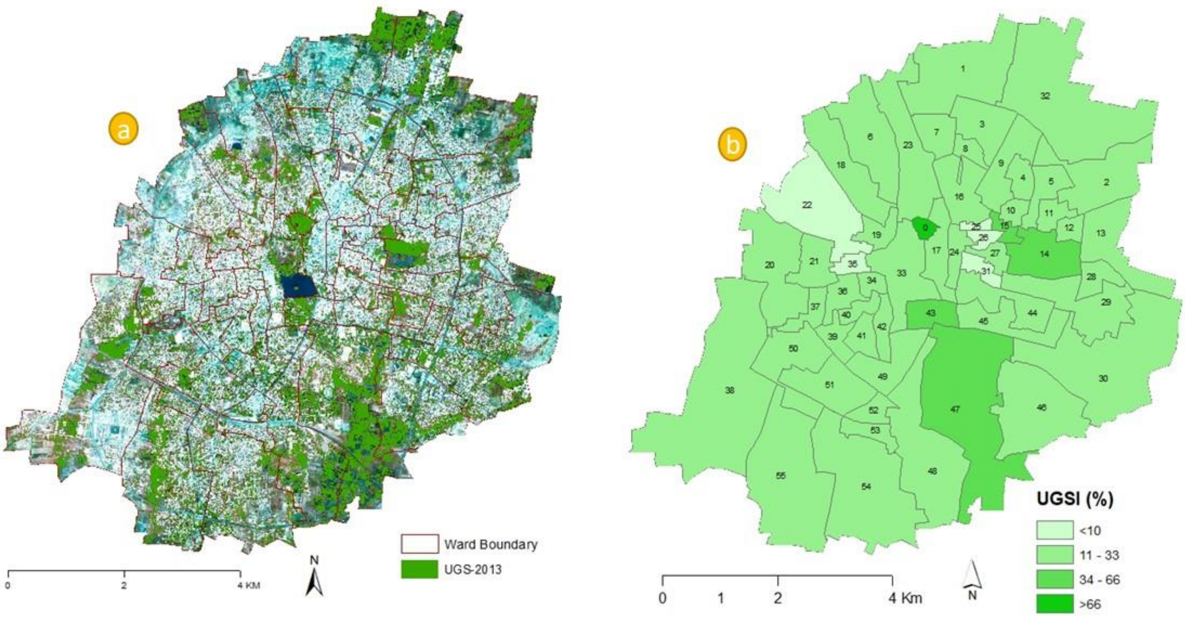


Figure 5. Urban Green Space Distribution: a) Urban Green Space at Ward level b) Urban Green Space Index expressed in percentage at ward level (Wards are numbered from 1 to 55 by the City municipal corporation)

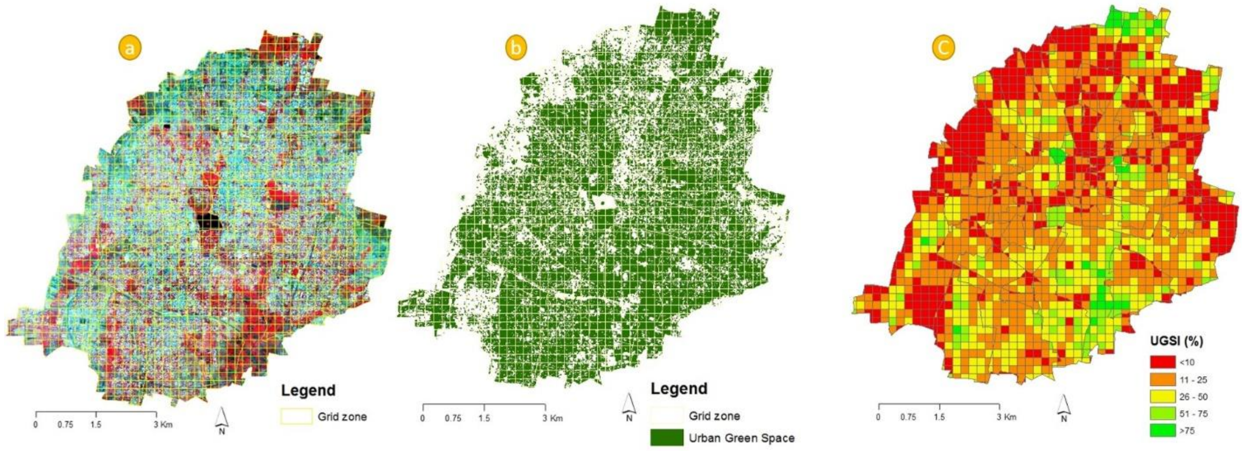


Figure 6. Grid zone level analysis: a) Grid zones overlaid on the ward map

b) Urban Green Space at Grid level c) UGSI expressed in % of green per grid zone

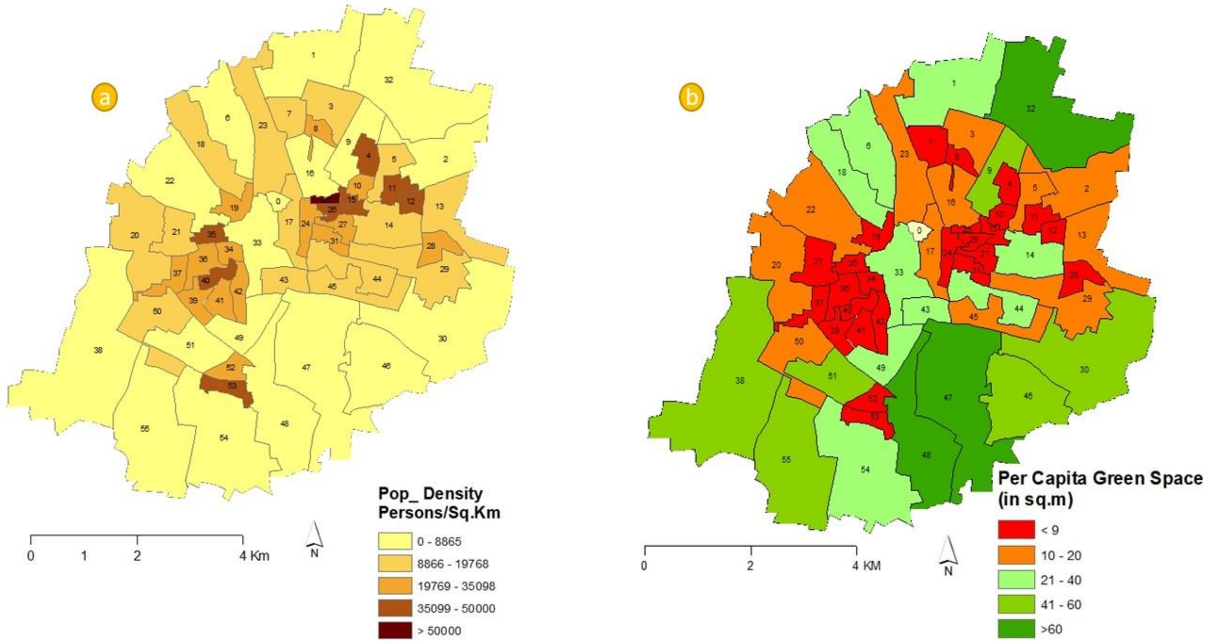


Figure 7. Relationship between population density and PCGS: a) Population density map of Kalaburagi City as per census of India, 2011 b) Per Capita Green Space of Kalaburagi city

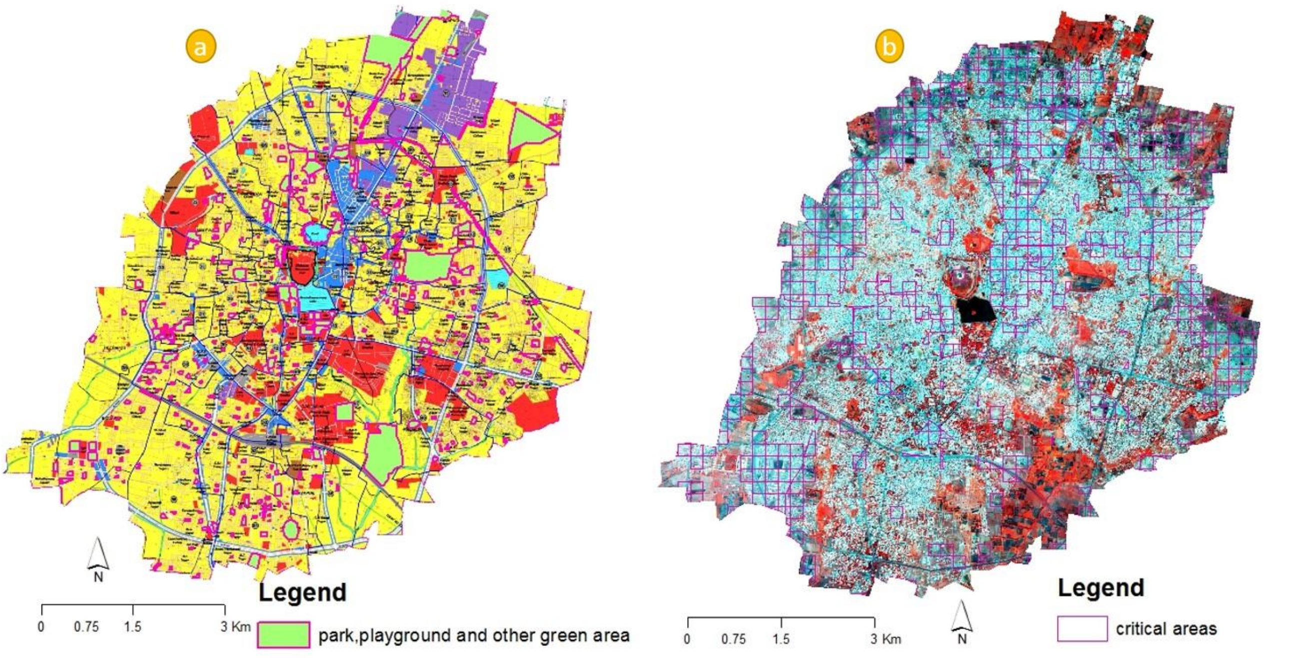


Figure 8 Improving the green space: a) Proposed land use map of Kalaburagi City (2020)

b) Grids have less than 10% of UGS overlaid on Geo Eye 2013 image

Table1 Population of Kalaburagi city

Census Year	Population
1981	221325
1991	310920
2001	430265
2011	543147

Source: Census of India (2011)

Table 2 Details of Satellite data

Satellite	Bits	Format	Spatial resolution	Spectral Bands	Date of capturing
GeoEye-1 Kalaburagi City	11-Bit	Geo TIFF	Panchromatic: 41 cm Multispectral: 1.65 m	B1-Blue: 450 - 510 nm B2-Green: 510 - 580 nm B3-Red: 655 - 690 nm B4-Near-IR: 780 - 920nm PAN 450 - 800 nm	07 Dec 2013

Source: Data Sheet, Digital Globe

Table 3 OBIA parameters

Process related Operation	Algorithm	Layers used at Pixel level/object level	GeoEye data (Kalaburagi)	
Image Segmentation (Step 1)	**Multi resolution segmentation**	B,R, G, NIR	**Scale: 30** Shape:0.5 Compactness: 0.5	
Classification (Step 2)	(i)Assign class (ii)Assign class **(iii)Chess board Segmentation**	Mean value of all layers NIR, R Object level ‘Green’	Brightness < 260 ‘Others’ NDVI > 0.5 ‘Green’ **Object size 4** Number of cycles1	
Basic Object Reshaping (Step 3)	Merge class	Object level	‘Green’	

Advanced Object Reshaping (Step 4)	Morphology	Object level	Open Image object Mask:5 circle	
Export (Step 5)	Export vector layer	Object level	Shapefile (*shp)	

Table 4 Description of Land cover classes

Class	**Class Description**
Green	The layer of leaves, branches and stems of tree that cover the ground when viewed from above. Grass, shrubs, lawns and other grass covered areas found in parks, golf courses and play grounds (Marvin Bauer, 2011)
Others	Impervious surfaces include shadows, building footprints, drive ways, sidewalks, parking lots, barren earth and other impermeable surfaces that are not obscured by tree cover (Marvin Bauer, 2011)

Table 5a Accuracy assessment result of GeoEye Image based on samples

		Reference data		
		Green	Un classified	Row Total
Classified Data	Green	1045	0	1045
	Unclassified	56	0	56
	Column Total	1101	0	1101

Producer's Accuracy
Green= 1045/1101 = 94.9% (5.1% Omission Error)
User's Accuracy
Green= 1045/1045= 100% (No commission error)
Overall Accuracy: 1045/1101 = 95%

Table 5b Accuracy assessment result of GeoEye Image based on TTA

		Reference data		
		Green	Un classified	Row Total
Classified Data	Green	1196537	0	1196537
	Unclassified	2001	0	2001
	Column Total	1198538	0	1198538

Producer's Accuracy

Green= 1196537/1198538 = 99.8% (0.2% Omission Error)
User's Accuracy
Green= 1196537/1196537= 100% (No commission error)
Overall Accuracy: 1196537/1198538 = 99.8%

Table 6 Distribution of UGSI in Kalaburagi at ward level

Urban Green Space	Ward Numbers (arranged in descending order based on the percentage of green space)
Less than 10%	26, 25, 22,31,35
11- 33%	16,12,24,8,34,7,11,20,3,36,6,21,37,40,52,2,53, 13,39,27,41,19,38,42,50,1,29,28,4,30,23,17,9, 5,10,45,33,54,18,49, 51,44,55,32,46,48
34-66%	14,15,43,47

Table 7 Distribution of UGSI in Kalaburagi at grid level

Urban Green Space	Number of grid zones
Less than 10%	733
10-25%	829
25-50%	506
50 -75%	157
Above 75%	52

Table 8 Distribution of PCGS in Kalaburagi at ward level

Per Capita Green Space (PCGS) in m^2	Ward Numbers (arranged in descending order based on the PCGS)
Less than 9	25,26,35,12,40,24,11,8,4, 36, 34,31,53, 52,27,37,42,28,19,7,21,39,10,15,41
10-20	13,22,5,3,20,45,23,16,17,50,2,29
21-40	18,6,1,14,33,43,44,49,54
41-60	55,38,30,9,46,51
Above 60	32,48,47